IMAGE RESTORATION FOR REDUCING BLOCK ARTIFACTS BASED ON ADAPTIVE CONSTRAINED OPTIMIZATION

By

AVIJIT KUNDU

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY KANPUR

August, 1999

IMAGE RESTORATION FOR REDUCING BLOCK ARTIFACTS BASED ON ADAPTIVE CONSTRAINED OPTIMIZATION

A Thesis Submitted
in Partial Fulfillment of the Requirements for the Degree of
P G D I I T

by

Avijit Kundu
(Roll No 9812401)

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY
KANPUR
AUGUST 1999

CERTIFICATE

This is to certify that the thesis work entitled **Image Restoration for Reducing Block Artifacts Based on Adaptive Constrained Optimization**' by *Avijit Kundu* (Roll No 9812401) has been carried out under my supervision and the same has not been submitted elsewhere for a degree

August 1999

Dr Govind Sharma
Associate Professor
Department of Electrical Engineering
Indian Institute of Technology Kanpur

Acknowledgements

I express my sincere thanks to my thesis superviser Dr Govind Sharma for his invaluable guidance and encouragement given to me throughout my thesis work

I am thankful to N Ramana, Vijay kumar Md Kasim, P R. Sahu for helping me whenever I faced problems during my thesis work in computer

I wish to thank my friends Ramana,M S Babu D Biswas R Sharma, R.Mandal for their support extended to me

I express my gratitude to the Department of DOORDARSHAN for giving me an opportunity to pursue this P G Course

Last but not the least I wish to acknowledge the constant encourangement, support, blessings and guidance which my parents gave me

Contents

List of Figures

Abstract

In some important image coding techniques such as transform coding, an image is divided into several no of blocks and then each block is coded indepedently One of the drawbacks of Discrete Cosine Transform (DCT) is visible block boundaries due to coarse quantization of the coefficients In this thesis an adaptive image restoration filter using DCT-based edge classification has been proposed for reducing block artifacts in compressed images Edge direction of each block is classified by using DCT coefficients and an adaptive constrained least square (CLS) filter along the edge direction is used for filtering the corresponding block Computer simulations have been used to evaluate the performance of the proposed restoration filtering technique

Chapter 1

Introduction

Digital image processing refers to processing of a two-dimensional picture by a digital computer Representing an image in digital form requires a large no of bits With the rapidly growing applications the total volume of digital images produced each day is increasing As a result, it has become necessary to find efficient representation for digital images in order to reduce the no of bits, bandwith of the the transmitting channel, etc Digital image coding is used in a variety of contexts, including conservation of bandwith in transmitting images and conservation of memory space in storing images The objective of image coding is to represent the image with as few bits as possible while retaining the sufficient picture information in reconstruction For effiecient transmission of digital networks, digital video needs to be compressed to meet the bandwidth constraints As the demand for video communication has grown, many effiecient image compression techniques have been developed and standardized Especially, good quality image communication with low bit-rate is gaining growing interests in applications to video conferencing, videophone, interactive TV etc When images are compressed at low bit-rate, images with more details usually degrade more than those with fewer details The original image is segmented into blocks, usually of equal size and then each block is coded independently Discrete Cosine Transform (DCT) is among the most popular transform technique for image processing because of its significant energy compaction property[11,13] and ease of implementation The main drawback of the block discrete cosine transform (BDCT) based compression technique is blocking artifact[2] which results from the

independent processing of the blocks without taking into account the block pixel correlations and produces artificial discontinuity between adjacent blocks(fig 5 2) The lower the bit-rate, the more severe the blocking artifacts due to loss of information Decoded images exhibiting blocking effects can be unpleasant to a viewer As the bit rate is reduced, the blocking effect, which is not noticeable at high bit rates, becomes more prominant

Ther are many methods available for reducing the blocking artifacts For example, in the overlap method abrupt discontinuities caused by coding can be reduced because the segmentation process weaves the adjacent subimages together[1] The overlap method reduces the blocking effects well without degrading the image content The major disadvantage of this method is increase in bit-rate based on images In the iterative image restoration methods the image quality can be improved significantly with sufficient number of iterations[3,5,6] But because of its slow convergence this method is not suitable for real-time processing Even in JPEG slow convergence is definitely a disadvantage

Here a post-processing technique has been used to reduce the blocking artifacts In order to reduce blocking artifacts effieciently, edge direction of each block is classified by using DCT co-efficients and an adaptive constrained least square (CLS) filter along the edge direction is used for filtering the corresponding block For real-time application, the proposed restoration filter is implemented in the form of a truncated FIR filter, which is suitable for postprocessing the images in real time video systems such as HDTV or video conferencing

The thesis is organised in the following way Chapter 2 gives the degradation model for the blocking artifacts Chapter 3 gives the adaptive image restoration based on the degradation model described in chapter 2 FIR implementation of the proposed algorithms for real-time processing is described in chapter 4 Finally simulation results and conclusions are given in chapter 5 and 6 respectively

Chapter 2

Degradation Model for Block Artifact

In digital image processing a two dimensional image is segmented into blocks, usually of equal size and each block is coded independently The purpose of image coding is to represent the image with as few bits as possible while retaining the sufficient picture information

Here an N×N image x(m,n) is divided into subimages of size B×B called blocks One dimensional representation of an N×N image x(m,n) for B×B block based processing,

$$x = [x_1^T \; x_2^T, \qquad , x_{N^2/B^2}^T]^T \tag{2 1}$$

where x_k for $k = (p-1)(N/B)+q$ represents the lexicographically ordered B^2 elements in the (p,q)th block Block diagram of the image degradation for the BDCT-based compression-reconstruction process is shown in fig 2 1

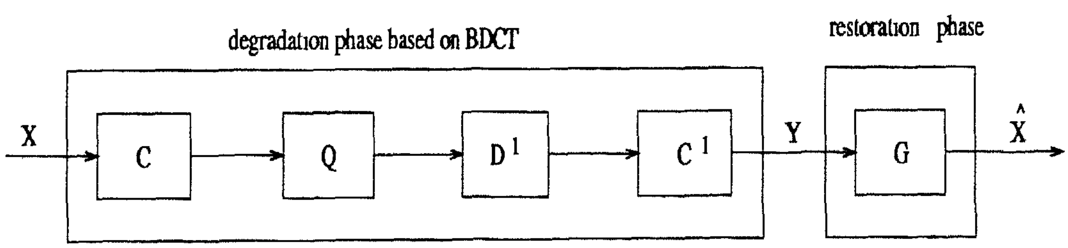

Figure 2 1 Block diagram of degradation restoration model for the BDCT based compression-reconstruction process

The degradation model can be expressed as

$$y = C^{-1}D^{-1}QCx \tag{2 2}$$

where y represents the reconstructed image with block artifacts due to quantization of BDCT coefficients, C and C^{-1} respectively, the block based forward and inverse DCT matrices and Q and D^{-1}, respectively, the corresponding quantization and the inverse quantization matrices The restoration phase represents the post filtering process for reducing block artifacts Based on the image representation model given in eqn (2 2), the above mentioned matrices can be represented as

$$C = \begin{bmatrix} [c_1] & 0 & 0 \\ 0 & [c_2] & 0 \\ 0 & & 0 \\ 0 & & 0 \\ 0 & & [c_{N^2/B^2}] \end{bmatrix} \tag{2 3}$$

$$C^{-1} = \begin{bmatrix} [c_1]^{-1} & 0 & 0 \\ 0 & [c_2]^{-1} & 0 \\ 0 & & 0 \\ 0 & & 0 \\ 0 & & [c_{N^2/B^2}]^{-1} \end{bmatrix} \tag{2 4}$$

where $[c_k]$ and $[c_k]^{-1}$, respectively represents the forward and inverse DCT matrices, with size $B^2 \times B^2$, for processing lexicographically ordered B×B image blocks The quantization operator is further divided into two successive operations, division and rounding off, such as

$$Q = RD \tag{2 5}$$

In eqn (2 5), the division matrix D can be written as

$$D = \begin{bmatrix} [d_1] & 0 & 0 \\ 0 & [d_2] & 0 \\ 0 & & 0 \\ 0 & & 0 \\ 0 & & [d_{N^2/B^2}] \end{bmatrix} \tag{2 6}$$

where the kth diagonal submatrix $[d_k]$ is a diagonal matrix whose diagonal elements are determined by the following way For a JPEG based quantization table as shown in fig 2 2

	j=1	j=2						j=8
i=1	50	60	70	70	90	120	255	255
i=2	60	60	70	96	130	255	255	255
	70	70	80	120	200	255	255	255
	70	96	120	145	255	255	255	255
	90	130	200	255	255	255	255	255
	120	255	255	255	255	255	255	255
	255	255	255	255	255	255	255	255
i=8	255	255	255	255	255	255	255	255

Figure 2 2 A quantization table used for 8x8 DCT coefficients

diagonal elements of $[d_k]$ can be represented as

$$d_k(l,l) = \frac{1}{t(i,j)}, \; for \; l = (i-1)\,8 + j, \; 1 \leq (i,j) \leq 8 \qquad (2\ 7)$$

where $t(i,j)$ represents the (i,j)th value in quantization table Rounding operation R can be written as a diagonal matrix whose diagonal elements performs rounding operation to the corresponding elements of input vector The inverse quantization matrix, denoted by D^{-1}, simply represents the inverse of the division matrix D

Chapter 3

Proposed Adaptive Image Restoration

Based on the degradation model described in the previous section an adaptive image restoration has been formulated In subsequent sections restoration algorithm and an edge classification algorithm using DCT coefficients is proposed

3 1 Proposed Image Restoration Algorithm

Equation (2 2) can be written as

$$y = C^{-1}D^{-1}QCx = Hx \tag{3 1}$$

where H can be considered as an image degration operator Many BDCT based moving image compression technique, such as H 261, MPEG 1 and MPEG 2 have the same block artifacts when the bit rate becomes less than the certain threshold value It is known that moving images have larger application areas than still images and block artifacts in moving images may degrade the quality of images more severely because block artifacts appear at the instance of rapid scene change For removing block artifacts in motion images, the iterative or optimization based type restoration algorithm are not suitable due to their slow convergence Even in still image application, slow convergence is definitely a disadvantage

For this reason a fast image restoration algorithm using classification based constrained optimization has been proposed for reducing block artifacts in BDCT-based compressed

images A general image restoration process based on the constrained optimization approach is to find x which satisfies

$$||y - Hx|| = 0 \tag{3 2}$$

subject to

$$||A\hat{x}||^2 \leq e^2 \tag{3 3}$$

where A represents a high pass filter and inequality equation(3 3) guarantees that high frequency component in the solution is controlled below the pre-specified quaantity The functional in eqn (3 2) represents the energy of the residual The original undegraded image x, the reconstructed image y with block artifacts and many other images can be elements of the solution set defined by eqn (3 2) One way to select a solution is to keep variance across the block boundary less than a certain value by appropriately choosing a space-variant high pass-filter in eqn (3 3) The degradation operator H in the BDCT-based compression reconstruction process is nonlinear and space-variant due to their nature of the rounding matrix Therefore an approximated version of the constrained optimization has been proposed, which minimizes

$$||y - H_L x||^2 \tag{3 4}$$

with respect to x, subject to

$$||A_E \hat{x}||^2 \leq e^2 \tag{3 5}$$

Here H_L is assumed as a space invariant low-pass filter and A_E is assumed as a block-adaptive directional high pass filter whose direction is determined by block-classified edge information DCT coefficients with higher frequency components tend to be more coarsely quantized Therefore H is considered as a low pass filter H_L Minimization of eqn (3 2) can suppress the smoothing operation on non boundary region in the image A_E smoothes the block boundaries while preserving directional edges which are not the results of the degradation process of the block coding The detailed process of block-based edge classification technique is described in the following section

3 2 Blocked-based Edge Classification

A block-classification technique using a part of DCT coefficients has been described which is used for implementing the block-adaptive directional high-pass filter in equation(3 5) For a B×B image block, the corresponding DCT coefficients are expressed as[12]

$$C_x(k_1, k_1) = c(k_1)\, c(k_2) \sum_{n_1=0}^{B-1} \sum_{n_2=0}^{B-1} x(n_1, n_2) cos\frac{\pi}{2B} k_1(2n_1+1) \times cos\frac{\pi}{2B} k_2(2n_2+1), \quad (3\ 6)$$

where

$$c(k) = \begin{cases} \sqrt{\frac{1}{B}} & \text{for k=0,} \\ \sqrt{\frac{2}{B}} & \text{for k=1,2, B-1} \end{cases} \quad (3\ 7)$$

For block size of 8×8, only $C(0,1)$ and $C(1,0)$ have been used out of sixty four DCT coefficients which represent vertical and horizontal edges respectively[4] These are given as

$$C_{ver} = C(0,1) = \frac{\sqrt{2}}{8} \sum_{n_1=0}^{7} \sum_{n_2=0}^{7} x(n_1, n_2) cos\frac{\pi}{2 \times 8} 2(n_2+1), \quad (3\ 8)$$

$$C_{hor} = C(1,0) = \frac{\sqrt{2}}{8} \sum_{n_1=0}^{7} \sum_{n_2=0}^{7} x(n_1, n_2) cos\frac{\pi}{2 \times 8} 2(n_1+1) \quad (3\ 9)$$

Using above two equations the directions of the edges in each block has been determined The edges of the 8×8 block is classified into monotone, horizontal, vertical, $0^0 \sim 45^0, 45^0 \sim 90^0, 90^0 \sim 135^0$,and $135^0 \sim 180^0$ edges The edge classification algorithm[4] is given in the following

Algorithm 1 (Edge classification)

If $|C_{ver}|\ |C_{hor}| \leq \sigma^2$, then the block is monotone,

else if $|C_{ver}| > \sigma$ and $|C_{hor}| \leq \sigma$, then vertical edge exists,

else if $|C_{ver}| \leq \sigma$ and $|C_{hor}| > \sigma$, then horizontal edge exists,

else if $C_{ver}\ C_{hor} > \sigma^2$ and $|C_{ver}| > C_{hor}$, then $0^0 \sim 45^0$ edge exists

else if $C_{ver}\ C_{hor} > \sigma^2$ and $|C_{hor}| > C_{ver}$, then $45^0 \sim 90^0$ edge exists,

else if $C_{ver}\ C_{hor} \leq \sigma^2$ and $|C_{hor}| > C_{ver}$ then $90^0 \sim 135^0$ edge exists,

else $135^0 \sim 180^0$ edge exists

Here σ is a positive quantity(0 001 $\sim$ 25 0) which controls the sensitive of edge classification

Chapter 4

FIR Implementation For Real-time Processing

According to image degradation model descrined earlier, the degradation operator H results in both discontinuities on block boundaries and loss of high frequency details inside blocks Among many practical applications of image restoration,the constrained least squares (CLS) restoration filter is widely used because it can incorporate a priori constraints into the restoration process The frequency response of a typical CLS restoration filter is given by [4]

$$G(k,l) = \frac{H^*(k,l)}{|H(k,l)|^2 + \lambda |A(k,l)|^2} \quad (4\ 1)$$

where $H(k,l)$ and $A(k,l)$ respectively represent the two-dimensional (2D) Discrete Fourier Transform (DFT) of the degradation operator and a high pass filter In the denominator of $G(k,l)$ in equation(4 1), $|H(k,l)|^2$ tries to reduce the degradation due to H, $|A(k,l)|^2$ suppresses excess amplification of high-frequency components and the Lagrange multiplier λ is determined such that the solution satisfies the equality in eqn (3 3) subject to eqn (4 1) As discussed earlier degradation due to quantization of BDCT coefficients is neither linear nor space-invariant and as a result, the CLS restoration filter cannot be implemented This is why we apply low pass filtering inside blocks and high pass filtering on block boundaries The first low pass filtering function is modeled by an approximated linear space-invariant

filter whose point spread function (PSF) is given as [4]

$$h_L(m,n) = \frac{1}{22}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 10 & 2 \\ 1 & 2 & 1 \end{bmatrix} \quad (4\ 2)$$

For a specific block with a certain edge type, denoted by the subscript E, the low-pass filtering degradation can be restored by the following approximated CLS restoration filter

$$G_E(k,l) = \frac{H_L^*(k,l)}{|H_L(k,l)|^2 + \lambda|A_E(k,l)|^2}, \quad (4\ 3)$$

where $H_L(k,l)$ and $A_E(k,l)$ respectively represent the 2D DFT of $h_L(m,n)$ and the directional high-pass filter $a_E(m,n)$, $E \in [mono, ver, hor, 45^0, 135^0]$ with proper zero padding [7,10] to make it 8×8 The point spread functions for different high pass filtering are given as[4]

$$a_{mono}(m,n) = \frac{1}{16}\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \quad (4\ 4)$$

$$a_{ver}(m,n) = \frac{1}{48}\begin{bmatrix} -1 & -10 & -1 \\ 0 & 24 & 0 \\ -1 & -10 & -1 \end{bmatrix} \quad (4\ 5)$$

$$a_{hor}(m,n) = \frac{1}{48}\begin{bmatrix} -1 & 0 & -1 \\ -10 & 24 & -10 \\ -1 & 0 & -1 \end{bmatrix} \quad (4\ 6)$$

$$a_{45}(m,n) = \frac{1}{4}\begin{bmatrix} 0 & 0 & -1 \\ 0 & 2 & 0 \\ -1 & 0 & 0 \end{bmatrix} \quad (4\ 7)$$

$$a_{135}(m,n) = \frac{1}{4}\begin{bmatrix} -1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & -1 \end{bmatrix} \quad (4\ 8)$$

The low pass filter h_L in eqn (4 2) and each high-pass filter a_E are empirically chosen by considering the fact that the region of support should become as small as possible with satisfactory restoration performance In implementing $G_E(k,l)$ in eqn (4 3), the lagrange multiplier λ =150 has been used for monotone edge block and λ =75 has been used for the rest

By taking the inverse DFT (IDFT) of G_E(k,l) we obtain the coresponding spatial domain PSF $g_E(m,n)$ with support B×B Then the PSF is truncated by the 2D raised cosine of size M×M, M<N[8]

$$w[m,n] = \frac{sin\frac{\pi}{N}(m-\frac{M-1}{2})}{\frac{\pi}{N}(m-\frac{M-1}{2})}\left[\frac{cos\frac{\pi}{N}\psi(m-\frac{M-1}{2})}{1-\frac{4\psi^2}{N^2}(m-\frac{M-1}{2})^2}\right] \times \frac{sin\frac{\pi}{N}(n-\frac{M-1}{2})}{\frac{\pi}{N}(n-\frac{M-1}{2})}\left[\frac{cos\frac{\pi}{N}\psi(n-\frac{M-1}{2})}{1-\frac{4\psi^2}{N^2}(n-\frac{M-1}{2})^2}\right] \tag{4 9}$$

where $\psi(0\sim 1)$ is the roll off factor Value of M is such that the size of the resulting filter is minimized with proper bandpass characterstics maintained The procedure for obtaining adaptive restoration filter is explained in fig 4 1

An adaptive restoration filter in an arbitrary direction is obtained by using five different $g_E(m,n)$ such as[4]

$$g(m,n) = \alpha\, u(m,n) + (1-\alpha)\{\beta\, g_1(m,n) + (1-\beta)\, g_2(m,n)\}, \tag{4 10}$$

where $u(m,n)$ represents the 2D impulse $\beta \in$ [0,1] is the weight between $g_1(m,n)$ and $g_2(m,n)$, α is the scaling factor which normalizes $g(m,n)$ and g_1 and g_2 are determined by the following algorithm[4]

<u>Algorithm 2 (Choice of two directional restoration filters)</u>

According to the edge classification algorithm given in Algorithm 1

(i) $g_1 = g_2 = g_{mono}$, for monotone edge

(ii) $g_1 = g_2 = g_{ver}$, for vertical edge

(iii) $g_1 = g_2 = g_{hor}$, for horizontal edge

(iv) $g_1 = g_{ver}$ and $g_2 = g_{45}$, for $0^0 \sim 45^0$ edge

(v) $g_1 = g_{45}$ and $g_2 = g_{hor}$, for $45^0 \sim 90^0$ edge

(vi) $g_1 = g_{hor}$ and $g_2 = g_{135}$, for $90^0 \sim 135^0$ edge

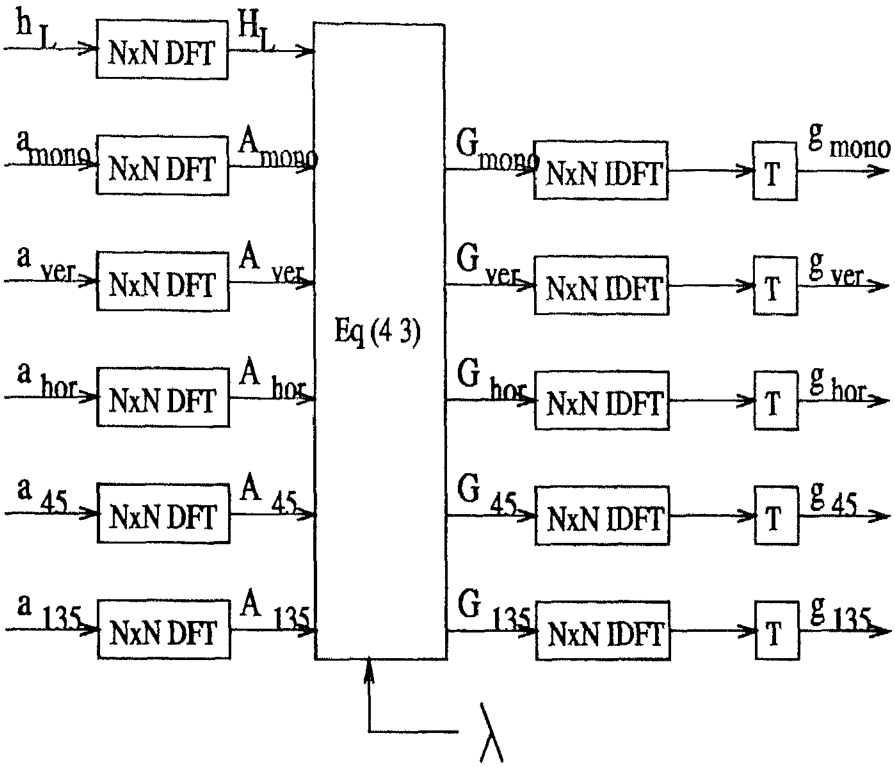

Figure 4 1 Procedure for obtaining five different FIR restoration filters,where blocks denoted by "T" represent truncation by the proper size of raised-cosine window

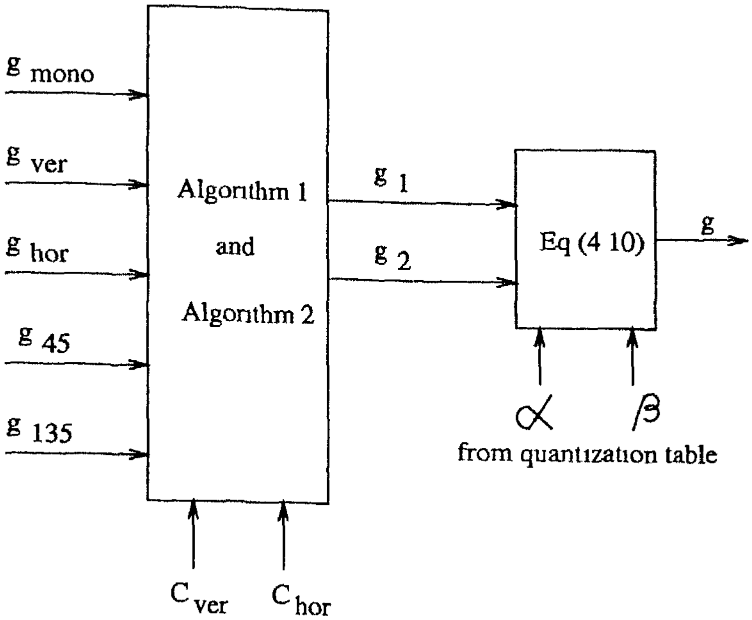

Figure 4 2 Procedure for implementing the adaptive FIR restoration filter for each block

(vii) $g_1 = g_{135}$ and $g_2 = g_{ver}$, for $135^0 \sim 180^0$ edge

In equation(4 9), β depends on the value of C_{ver} and C_{hor} and α depends on the (1,2)th and (2,1)th value in the quantization table as shown in fig 2 2

The procedure of implementing the adaptive FIR restoration filter for each block is shown in fig 4 2

It is to be noted here that $g_E(m\ n)$, $E \in [mono, ver, hor, 45^0, 135^0]$ can be obtained well before the restoration process starts In processing each block $g(m,n)$ for each block is computed by using the above two algorithms and the convolution of the corresponding block with the $g(m,n)$ is performed

Chapter 5

Simulation Results

The two algorithms described earlier have been developed using C programming Images of 256×256 pixel values have been considered and each image is again subdivided into no of blocks of size 8×8 The 256×256 Lena image has been compressed and then reconstructed by computer simulation according to the degradation model shown in fig 2 1 In the degradation process, a JPEG quantization table has been used as shown earlier in fig 2 2 Original and the compressed images have been shown in figures 5 1, 5 2 and 5 6 using two different quantization factors,Q 1 and 1 5 Different edges have been classified using algorithm 1 and five different restoration filters in different directions have been developed by using algorithm-2 Lena image has been processed by those five different restoration filters The resulting block artifacts reduced Lena images have been shown in figures 5 3, 5 4, 5 5, 5 7, 5 8, 5 9 using two different quantization factors,Q When the subjective quality is compared it is evident that the restored image by using five different restoration directional filters is the winner in the sense of both reducing block artifacts and preserving edge details inside each block For each quantization factor,Q three different restored Lena images have been shown for three different values of scaling factor α (0 4, 0 6, 0 75) used in the equation(4 10) It has been observed that removing the blocking artifacts completely results in the increase in blurring in the restored images Considering this fact a compromise has to be made between blocking artifacts and blurring in the pictures

Another image of Claire (fig 5 10) of size 256×256 has been considered and the same has been

Figure 5 1 Original Lena image

compressed and processed for the same quantization factor,Q and for three different values of scaling factor α as mentioned earlier using algorithm 1 and algorithm 2 Corresponding to those different values of Q and α compressed and processed Claire images also have been shown in figures 5 11, 5 12, 5 13, 5 14, 5 15, 5 16, 5 17, 5 18

Figure 5 2 Compressed Lena image with quantization factor Q=1

Figure 5 3 Processed Lena image with Q=1 and α=0 4

Figure 5 4 Processed Lena image with Q=1 and α=0 6

Figure 5 5 Processed Lena image with Q=1 and α=0 75

Figure 5 6 Compressed Lena image with quantization factor Q=1 5

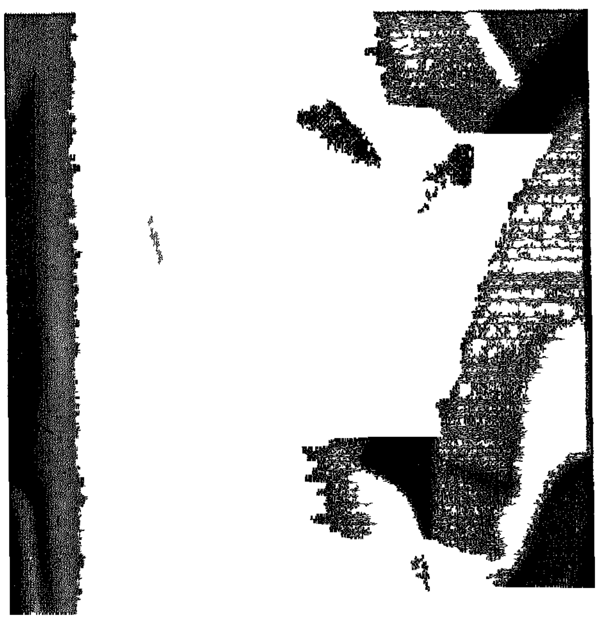

Figure 5 7 Processed Lena image with Q=1 5 and α=0 4

Figure 5 8 Processed Lena image with Q=1 5 and α=0 6

Figure 5 9 Processed Lena image with Q=1 5 and α=0 75

Figure 5 10 Original Claire image

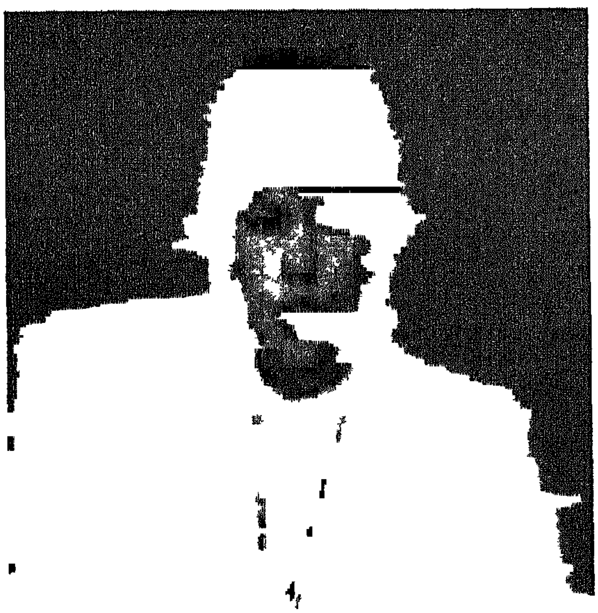

Figure 5 11 Compressed Claire image with quantization factor Q=1

Figure 5 12 Processed Claire image with Q=1 and α=0 4

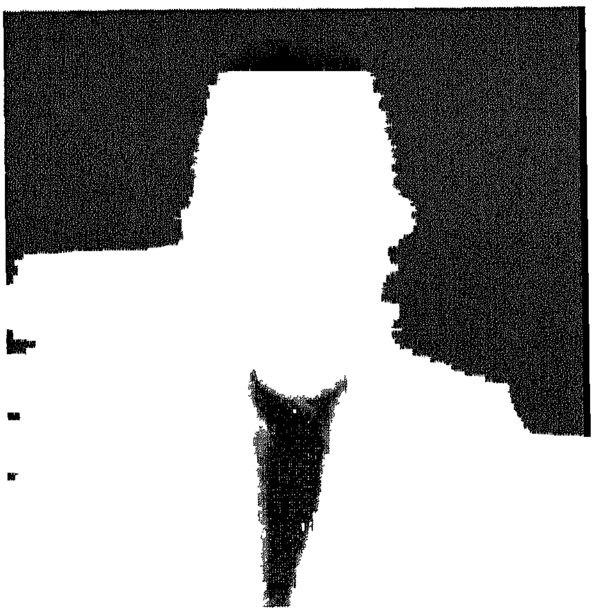

Figure 5 13 Processed Claire image with Q=1 and α=0 6

Figure 5 14 Processed Claire image with Q=1 and α=0 75

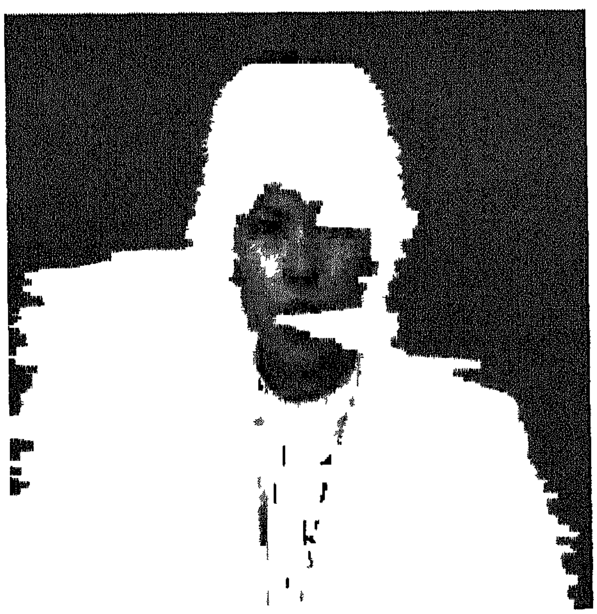

Figure 5 15 Compressed Claire image with quantization factor Q=1 5

Figure 5 16 Processed Claire image with Q=1 5 and α=0 4

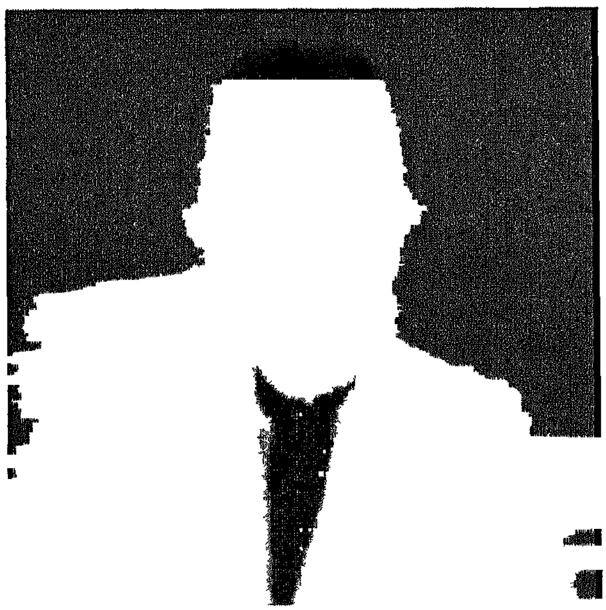

Figure 5 17 Processed Claire image with Q=1 5 and α=0 6

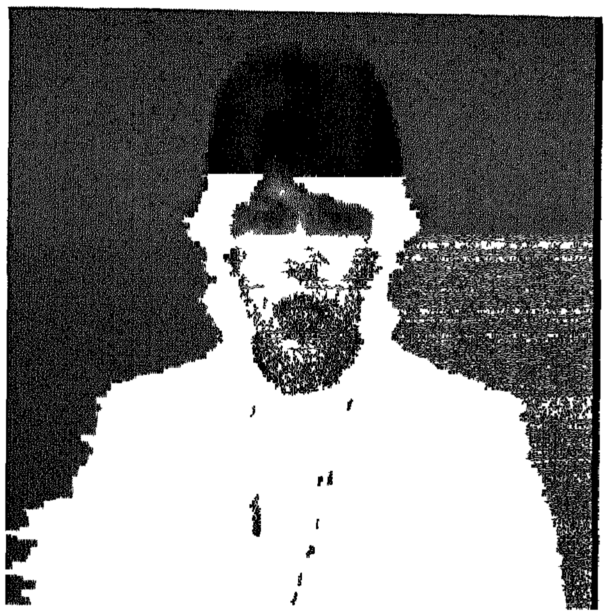

Figure 5 18 Processed Claire image with Q=1 5 and α=0 75

Chapter 6

Conclusion

In this thesis an adaptive image restoration filter for reducing block artifacts has been developed in BDCT based compressed images Although the proposed restoration filter can efficiently reduce the block artifacts, the quality of the processed image is not as good as that of the original one due to missing information in the quantization process and the inherent low-pass characteristics in the proposed filter The major contribution of this thesis is that it enables real time constrained optimization processing for reducing block artifacts by using simple edge classification technique In comparing the proposed algorithm with conventional iterative type algorithms, which are used mainly for still images, there is no significant degradation in the proposed image while the computation time is greatly reduced

6 1 Scope for Future Work

In this thesis the whole work has been done with achromatic images only This can be extended to color images also Though the work has been done with stored still images only, this work can be carried out in real-time processing also The algorithms used here can be used in many applications like edge detection in JPEG, MPEG, etc The edge detection process described earlier can be extended to extract more complex feature of the still images and moving images The proposed filter may be used as a postprocessor in the decoder of moving image compression systems, such as digital VCR, video on demand,

digital HDTV systems, medical processing etc Some works can be carried out to find more effective algorithms which will work adaptively according to the quantization matrix and the characteristics of the source iamge

References

[1] Howard C Reeve and Jae S Lim, " Reduction of Blocking Effects in Image Coding", *Optical Engineering*, Vol 23, No 1, Jan /Feb , 1984

[2] Mei-yin Shen and C C Jay Kuo, "Review of Postprocessing Technique for Compression Artifact Removal", *IEEE Trans on Consumer Electronics*, Vol 40, No 3, August, 1994

[3] A K Katsaggelos, "Iterative image restoration algorithm", *Optical Engineering*, Vol 28, No 3, July, 1989

[4] Tae Keun Kim and Joon Ki Paik, "Fast Image Restoration for Reducing Block Artifacts Based on Adaptive Constrained Optimization", *Journal of Visual Communication and Image Representation*, Vol 9, No 3, September,1998

[5] Avideh Zakhor, "Iterative Procedures for Reduction of Blocking Effects in Transform Image Coding", *IEEE Trans on Circuits and Systems for Video Technology*, Vol 2, No 1, March,1992

[6] Yongyi Yang, Nikolas P Galatsanos and Aggelos K Katsaggelos , 'Regularized Reconstruction to Reduce Blocking Artifacts to Block Discrete Cosine Transform Compressed Images", *IEEE Trans on Circuits and Systems for Video Technology* Vol 3, No 6, December,1993

[7] Jain A K , *Fundamentals of Digital Image Processing*, Prentice-Hall of India, New Delhi, 1997

[8] Proakis J G and Dimitri G Manolakis, *Introduction to Digital Signal Processing*, Macmillan, New York, Collier Macmillan Publishers, London, 1988

[9] Gonzalez R C and Woods R E , *Digital Image Processing*, London, Addision-Wesley, 1977

[10] Oppenheim Alan V and R W Schafer, *Discrete time Signal Processing*, Prentice-Hall, New Jersey, Englewood Cliffs, 1989

[11] Murat Kunt, *Digital Signal Processing*, Norwood, Artech, 1986

[12] J S Lim, *2 Dimensional Signals and Image Processing*, Englewood Cliffs, Prentice Hall, 1990

[13] W K Pratt, *Digital Image Processing*, New York, John Wiley, 1978

A 130449

Date Slip

This book is to be returned on the date last stamped